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"Internet and enterprise productivity: evidence from Latin America"

Juan Jung, Enrique López-Bazo, Matteo Grazzi

Research Institute of Applied Economics
Regional Quantitative Analysis Research Group

I|R|E|A
Institut de Recerca en Economia Aplicada Regional i Públic
Research Institute of Applied Economics
WEBSITE: www.ub-irea.com • CONTACT: irea@ub.edu

AQR
Grup de Recerca Anàlisi Quantitativa Regional
Regional Quantitative Analysis Research Group
WEBSITE: www.ub.edu/aqr/ • CONTACT: aqr@ub.edu

Universitat de Barcelona
Av. Diagonal, 690 • 08034 Barcelona

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Abstract

This paper tests three hypotheses regarding the link between internet and firm productivity: i) internet adoption and use constitute a source of productivity growth for firms in Latin America, ii) the intensity of its use also matters, and iii) the link between the new technologies and productivity levels is not uniform over the whole productivity distribution. The evidence in this paper fills the gap of scarce and fragmented literature focused on Latin America, and is aligned with previous research for more developed regions which has generally recognized that Information and Communication Technologies (ICTs) have radically changed how modern business are conducted, benefitting firm performances through several channels, such as increasing the efficiency of internal processes, expanding market reach or increasing innovation. Our findings suggest that low-medium productive firms benefit more from an expansion in internet adoption and use, in comparison with the most productive ones. If this evidence is supposed to reflect long-term effects, then public policies oriented to massify internet adoption and promote internet use intensively will surely contribute to reduce inequalities of enterprise's productivity levels, promoting a level playing field among Latin American firms, something especially relevant for the most unequal region of the world.

JEL classification: D22, O31, O33, O54

Keywords: ICT, Internet, Productivity, firms, Latin America

Juan Jung. AQR-IREA, Universitat de Barcelona, Av. Diagonal 690, 08034 Barcelona, Spain. Tel: +34616963716. E-mail: juanjung@gmail.com

Enrique López-Bazo. AQR-IREA, Universitat de Barcelona, Av. Diagonal 690, 08034 Barcelona, Spain. Tel: +34934037041. E-mail: elopez@ub.edu

Matteo Grazzi. Competitiveness, technology and innovation division - Inter-American Development Bank, 1300 New York Avenue, NW 20577 Washington DC, USA. Tel: +12029428235. E-mail: matteog@iadb.org

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1. Introduction

Over the last decades, the economic literature has progressively recognized the links between Information and Communication Technologies (ICTs) and economic growth. In particular, a large body of research has clearly shown the relationship between the acceleration of productivity growth and ICT diffusion in the context of growth accounting (Oliner and Sichel, 1994 and 2002; Jorgenson, 2001).

Firms are the economic units where this relationship effectively takes place. ICT adoption can be related to improvements in business performance through various channels. ICTs allow faster communications and quicker processing of information, decreasing internal coordination costs, and facilitating the decision making processes (Cardona et al, 2013; Arvanitis and Loukis, 2009; Atrostic et al, 2004; Gilchrist et al, 2001). ICTs may also promote substantial firm restructuring, making internal processes more flexible and rational, and reducing capital requirements, by improving equipment utilization and inventory reduction. Moreover, the possibility of developing better communication channels with suppliers, clients, knowledge providers, and competitors may increase innovation capacities.

As a result, ICTs seem to allow firms to use new processes and business practices which, in turns, are linked to performance improvements. However, ICT-driven productivity gains are expected to vary largely across countries, regions, industries, and even between enterprises within the same industry and economy, suggesting that simple diffusion may be not sufficient to take full advantage of the potential of ICTs. Empirical evidence indicates that firm-specific operational and organizational characteristics determine the expected benefit deriving from ICT adoption. Therefore, complementary investment in areas such as organizational change and human capital appear necessary to both increasing absorptive capacity and maximizing the real impact of new technologies (Brynjolfsson and Hitt, 2000). Institutional framework and other environmental factors may also be crucial in exploiting ICTs full potential.

Given the complexities described above, it is a key element to understand more about the link of ICT with productivity, and whether the strength of this link varies across firms. A complete understanding of these dynamics is central in order to design effective public policies to promote ICT adoption and increase firm productivity. Past research has already suggested that the effect of ICTs on economic performance may vary across different economic agents, although main evidence has been developed at a country-level (see for instance Thompson and Garbacz, 2011; Qiang et al, 2009; or Fernández-Ardèvol et al, 2011), while firm-level analysis is still scarce, being the most relevant recent contribution that of Paunov and Rollo (2016).

Clearly, the concept of ICT includes a variety of different technologies and applications, with different potential impact on firm's performance (hardware, software, telecommunications, etc). Recently, broadband internet connection has been indicated as one of the most effective, because of its potential to enable a wide set of productivity-enhancing services. Some authors stated that broadband has become a necessary infrastructure for economic and social development, as it has happened before with advances such as railroads, roads, and electricity (Mack and Faggian, 2013; and Jordan and De León, 2011). As a result of that, while inspired in ICTs in general, our analysis will focus exclusively in the adoption and use of internet, as it has emerged as the main component of these technologies nowadays.[2]

Rather than exploring the impact of internet based on aggregated data (at country, region, or industry levels), this paper assesses its distributional effects at the firm-level. This is a key aspect since having a complete understanding of the distributional effects is crucial for public policies. As stated by Frölich and Melly (2013), from a policy perspective, a public intervention that helps to raise the lower tail of an outcome distribution should be more appreciated than an intervention that shifts the median, even if the average treatment effects are similar. For instance, if the effect of increasing the use of internet was found to be stronger in low-productive firms, a policy intervention related to the adoption and use of these technologies –for instance, a national broadband deployment plan– will help reducing disparities among firms in productivity. On the contrary, if most productive firms were found to be mostly related to internet-derived gains, then a massification of these technologies would increase disparities among firms.

While the bulk of the literature has focused so far on developed countries, evidence from emerging economies is still scarce and dispersed. In this regard, some of the

[2] Given that variables about adoption of computers are unavailable in our sample, it's not possible to distinguish between effect of the Internet and a potential effect of other ICTs such as computers (not connected to the net).

most recent contributions have analysed the effect of ICTs on productivity exploiting the firm-level data from the World Bank Enterprise Survey (WBES) for specific groups of developing countries (e.g. Cirera et al, 2016; Paunov and Rollo, 2016). In a similar vein, this paper aims to contribute to this literature by exploring the relationship of internet with productivity in the context of the Latin America region, which constitutes an appealing case of analysis for a number of reasons. Firms in the region seem to be less innovative and productive when compared to those belonging to more advanced economies, and one possible reason is related to internet diffusion and use, which is still relatively low. In fact, although internet has significantly increased its diffusion in the region, there is still a notable divide between Latin America and the developed countries, especially in most advanced technologies. Although the region's GDP has been growing fast since the beginning of the 2000s -mainly driven by high commodity prices-, advances in productivity levels have been much poorer, and ICTs can surely provide a powerful opportunity to catch-up. On the other hand, Latin America is the region in the world with the highest levels of inequality. From that perspective, the possibility of finding out the distributional effects of internet, and the implications of public interventions aimed to foster the diffusion and use of this new technology, will surely constitute a useful input for policy makers.

This study provides important contributions to the literature. The possibility of performing an empirical analysis at a micro level –in contrast to one based on aggregated region/country/sector data– is especially relevant as firms are the main economic agent in the internet-productivity relationship. On the other hand, our measure of firm performance will be a Total Factor Productivity (TFP) indicator built following the procedure suggested by Levinsohn and Petrin (2003), instead of performing the analysis on less suitable measures as labour productivity.[3] To the best of our knowledge, this is the first effort to provide comprehensive evidence at a firm-level in Latin America about the effect of internet on TFP throughout the overall distribution of this indicator, not just at the mean, something which is crucial to provide inputs for public policies oriented to promote the adoption and intensive use of new technologies.

[3] Labour productivity is often seen as an incomplete measure of efficiency. On the contrary, TFP is a measure that captures efficiency considering all factor inputs, being as a result, a more complete indicator of the use of resources by productive agents.

Paunov and Rollo (2016) is the closest study to ours in terms of approach and scope. However, our study differs from theirs in a series of aspects. In the first place, theirs main focus is to study the effect of ICT-related industry spillovers on firm's labour productivity. In the second place, we will follow an Unconditional Quantile Regression approach (UQR; e.g. Firpo, 2007) in order to characterize the effect of internet on the firm's TFP throughout the overall distribution of productivity. In our opinion, this is a more appropriate choice when the aim is on the distributional impact of internet, as the estimated effects of internet in this case corresponds to the unconditional distribution of productivity, which is the variable of interest. In contrast, Paunov and Rollo (2016) apply the more conventional Conditional Quantile Regression approach (CQR; Koenker and Bassett, 1978), whose estimated effects refer to the conditional distribution of productivity, which may substantially differ from the actual (unconditional) one. Finally, theirs sample is composed by firms from emerging economies in general, while our analysis is particularly focused in Latin American enterprises.

Our study, however, encountered some limitations. Due to data unavailability, we are unable to perform panel-data estimations and, therefore, to control for unobservables that may affect productivity and internet at the same time, confounding the estimated effect as a result. On the other hand, the link between internet and productivity may be bidirectional, as high productive firms are more expected to adopt ICTs, and to make better use of them once adopted. To control for potential endogeneity, we implement an Instrumental Variables estimator (IV). However, this is only possible for the analysis at the mean of the distribution, as there has not yet been developed a similar consistent estimation procedure for the UQR approach. Therefore, although some robustness checks are performed to address the endogeneity concern, we should be cautious when deriving conclusions from the results in terms of causal effects.

The rest of the paper is organized as follows. In Section 2, we review the related theoretical and empirical literature, from where we will outline our main hypotheses. In Section 3, the dataset and variables to be used in the empirical analysis are presented. In Section 4, we include a descriptive analysis of the variables of interest. In Section 5, we specify the empirical model to explore the relationship between internet adoption and use on productivity. In Section 6, we discuss the main results of the empirical estimations. Finally, concluding remarks are provided in Section 7.

2. Literature Review and Hypothesis

The link between economic performance and ICTs has received considerable attention in the literature, and over the last few years, many firm-level empirical studies have identified multiple channels through which ICT can have a positive effect on enterprise performance. For example, Mack and Faggian (2013) stated that ICTs have dramatically changed every aspect of modern life, including business management, which has been revolutionized by the new capacity of finding, sharing, and storing information.

In fact, ICTs have the potential to generate a large impact on the internal communication processes of a firm. For example, it is usually argued that ICTs can help to reduce internal communication costs (Jorgenson, 2001), allowing quicker information processing, lower coordination costs, fewer supervisors required (reduction in labour costs), and an easier facilitation of the decision making process (Cardona et al, 2013; Arvanitis and Loukis, 2009; Atrostic et al, 2004; Gilchrist et al, 2001). In turn, the reduction in communication costs can spur additional investments (Colecchia and Schreyer, 2002). Moreover, ICTs may enable the development of new processes and new work practices (Mack and Faggian, 2013), and facilitate substantial firm restructuring (Brynjolfsson and Hitt, 2000), making internal processes more flexible and rational, and reducing capital requirements through better equipment utilization and inventory reduction. These improvements may also allow firms to improve the quality of their outputs. In addition, the adoption of ICTs opens the possibility to improve external communication channels with suppliers, clients and, other firms, facilitating innovation processes, arranging new distribution systems and prompting knowledge spillovers across firms and regions (Czernich et al, 2011). Cheaper information dissemination can facilitate the adoption of new technologies devised elsewhere. As knowledge is crucial for economic activity, the potential of ICT to generate more efficient external collaboration may promote the creation of new knowledge (Forman and Zeebroeck, 2010). From a market perspective, ICT development can contribute to lower entry barriers and to promote transparency, fostering competition and development of new products, processes and business models (Czernich et al, 2011).

As a result of all the above, ICTs have become a substantial part of the modern business environment (Cardona et al, 2013), allowing factor productivity gains in industries that are intensive in ICT utilization. In a seminal study, Brynjolfsson and Hitt (2003) explored the effect of computerization on productivity and output growth in a sample of US firms over the period 1987-1994, finding a positive relation. This relation has been confirmed through the years by several empirical studies in various contexts. For example, Hempell (2005) found significant evidence of the productivity effects of ICT using a generalized method of moments estimator on a panel data of German firms in the period 1994-1999. Arvanitis and Loukis (2009) and Kaiser and Bertschek (2004) confirmed those findings using data from Greece and Switzerland, and Germany, respectively. Among emerging regions, Cirera et al (2016) conducted a study based on a sample of Sub-Saharan African countries, following the CDM approach (Crepon et al, 1998),[4] finding positive and robustly significant impact of ICT on innovation, although the link to productivity was found to be less clear and dependent on the different innovation measures. For the Latin America region, Gutierrez (2011) found a positive and significant effect of ICT investments in labour productivity in Colombian manufacturing enterprises. Aboal and Tacsir (2015), for a sample of Uruguayan firms, found evidence of a positive association between ICT and productivity in manufacturing and services sectors. Alvarez (2016) found evidence of a positive contribution of ICT to productivity levels in a sample of Chilean enterprises. In this context, the first hypothesis in this paper is to check if this effect can be generalised to the entire set of firms in the Latin America region:

H1: Internet adoption and its use are a source of productivity gains for Latin American firms.

Beyond adoption and individual uses, the link of internet on productivity is possibly related to the intensity of its use. In this sense, using internet simultaneously in

[4] Since the seminal contribution of Crepon et al (1998), the CDM strategy has become popular in studies analysing the effect of the determinants of R&D, innovation, and productivity. In brief, it first model the determinants of R&D, then those of innovation, including R&D, and finally it considers the effect of innovation on productivity.

various aspects of business activity should be expected to be relevant beyond the individual uses. Thus, we can delineate the second hypothesis as:

H2: The higher the intensity of internet use, the greater the effect on productivity.

The impact of ICT may be conditioned to certain characteristics of the internal context of the firm. In particular, some authors have highlighted the importance of complementary investments, pointing out that ICT adoption may increase its productivity impact if combined with human capital investment or internal restructuring (Brynjolfsson and Hitt, 2000). Knowledge stock and skills constitute determinants of absorptive capacity, which may influence firm capabilities to make the most of new technologies (Benhabib and Spiegel, 1994; Cohen and Levinthal, 1990). Organizational complements and intangible assets are considered crucial for ICT influence on productivity.

External factors may also be important to determine the dimension of the impact. In fact, potential gains derived from ICTs may depend on the linkages of the firm with external organizations. Network externalities may also be present, when the benefits of having adopted a technology depend on the adoption decisions of other users. In the case of internet connection, it means that economic returns to connectivity should rise once a certain threshold of connectivity penetration in the society is achieved. On the other hand, the degree of impact of ICTs will surely depend on the firm's previous access to knowledge. As stated by Paunov and Rollo (2016), all else equal, firms that are connected to rich (poor) *offline* knowledge networks may possibly have fewer (stronger) productivity performance gains from adopting and using internet intensively. Moreover, by adopting and using ICTs, smaller firms may be able to perform tasks which previously were exclusive to the bigger ones, like enlarging its interactions with clients and suppliers, or to increase the scope of its diffusion activities. This is particularly relevant in the case of emerging regions, as ICTs may help lagging firms to overcome restrictions derived from the socioeconomic and institutional frameworks. Considering that, extending the use of ICTs to all enterprises in Latin America may contribute to reduce the productivity gaps across enterprises.

Previous research has already found some insights regarding heterogeneities in the impact of ICTs on economic performance. In a country-level analysis, Thompson and Garbacz (2011) found that broadband had a relatively more favorable economic impact in low-income countries than in high-income economies. In the same fashion, Qiang et al (2009) suggested that the growth effects of broadband, as well as those of other technologies, were higher in low-income countries than in high-income economies. According to Fernández-Ardèvol et al (2011), the economic impact of mobile phones was larger in Latin America than in OECD countries. Empirical evidence has also been found within most advanced regions. Cardona et al (2013) argued that ICTs contributed more to United States than to Europe's productivity, explaining that the reason behind this may be related to differences in organizational and managerial capabilities. On the other hand, Bloom et al (2012) found differences in the productivity of ICT capital across a sample of firms operating in the United Kingdom, reaching higher levels those US-owned establishments.

At a firm level, Paunov and Rollo (2016) found evidence of the positive impact of industry internet use spillovers on enterprise performance in emerging countries, and the benefit was higher for smaller firms, and those located in smaller agglomerations and non-exporters; although their quantile regressions analysis show that relatively larger benefits arose only for the most productive firms among those groups. However, they followed the CQR approach which refers to the effect in specific points in the output distribution conditional on the set of observable factors considered in the analysis. In other words, it measures the effect on different parts of the overall conditional productivity distribution. Conversely, our study estimates the effect on the unconditional productivity distribution to test the following hypothesis:

H3: The effect of increasing the internet adoption and use is stronger for low-medium productivity firms than for firms at the upper end of the productivity distribution. As a result, extending the use of this ICT technologies contributes to reduce productivity inequality in Latin American firms.

3. Dataset and variables

3.1 The Dataset

The data for the empirical analysis comes from the WBES database,[5] which provides representative samples of the population of firms in the private sector of the countries

[5] http://www.enterprisesurveys.org/about-us

covered. The surveys cover a broad range of topics relevant to business including, among others, innovation, ICTs, access to finance, corruption, infrastructure, crime, competition, and performance measures.

The WBES are answered through face-to-face interviews with top managers and business owners. Typically 1200-1800 interviews are conducted in larger economies, 360 interviews are conducted in medium-sized economies, and for smaller economies, 150 interviews take place. The manufacturing and services are the primary business sectors of interest for the survey.[6] Formal (registered) companies with 5 or more employees are targeted for interview. Firms with 100% government or state ownership are not eligible to participate. In each country, businesses in the cities or regions of major economic activity are interviewed.

The WBES follow a stratified random sampling, as all population units are grouped within homogeneous groups and simple random samples are selected within each one. The strata for the WBES are firm size, business sector, and geographic region within a country. Ideally the survey sample frame is derived from the universe of eligible firms obtained from the country's statistical office. Sometimes the master list of firms is obtained from other government agencies such as tax or business licensing authorities, while in some cases, the list of firms is obtained from business associations or marketing databases.

Since 2002, the World Bank has been collecting these data in over 155,000 companies in 148 economies. However, it is worth to mention that information is not available on a regular basis for all countries. While the WBES have been increasingly intending to produce panel-data, there is still some limitations in its availability. For instance, for Latin America, surveys were mainly conducted across two waves, 2006 and 2010, and while there are some firms that were surveyed in both years (conforming a panel), there is still some critical information missing from the first wave. Unfortunately, this is the case for most ICT and innovation related data.

Therefore, we will use the two-period panel (2006 and 2010) to conduct the TFP estimation, while due to information unavailability, the dataset to be used for our main empirical estimation linking TFP with internet-related variables will consist in a 2010

[6] This corresponds to firms classified with ISIC codes 15-37, 45, 50-52, 55, 60-64, and 72 (ISIC Rev.3.1).

cross-section sample of enterprises from 19 Latin American countries,[7] most of which belonging to the manufacturing sector.

3.2 Internet related variables

Table 1 summarizes the explanation for the internet-related variables available in the dataset, including the specific question from the survey questionnaire, as well as the answer options applicable for each case. The internet adoption variable consist in high-speed broadband being adopted by the firm. Therefore, this definition excludes the older and slower dial-up internet connections, which do not seem to be suitable for intensive uses in the period under analysis.[8] Additionally, we extend the analysis, by considering not only broadband adoption, but also the degree of exploitation of its potential, measured through a series of internet uses, which rank from those with lowest intensity (email), to those more sophisticated as research and development of ideas on new products and services. Theoretically, each of the variables exposed at Table 1 has the potential to improve firm efficiency and to increase productivity as a result. The email use can help enterprises to better communicate with clients and suppliers, making communications more efficient and reducing costs. Having an own website can help enterprises in its diffusion activities, on marketing purposes and to promote e-commerce, reducing intermediation costs and reaching a direct contact with clients. Moreover, the possibility of storing data from clients through its registry in a firm's website has enormous potential for marketing purposes. The use of internet to make purchases for the firm will surely help the internal purchasing departments to find out the better offers and prices, as well as reducing time and costs associated to intermediation. The use of internet for the delivery of services will surely improve logistic efficiency and reduce distribution costs. Finally, the possibility of using internet to perform research activities can help the firms in developing ideas on new products and services, which can later become innovations, which in turn can help increase productivity. Although there are much more possible ICT uses that may contribute to firm performance improvements, those offered by the survey can provide

[7] Argentina, Bolivia, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, México, Nicaragua, Panamá, Paraguay, Perú, Trinidad and Tobago, Uruguay and Venezuela.

[8] However, within the broadband category, there could still be very big differences in the quality of the connections, that we cannot capture with this data.

us some serious empirical evidence on the link between internet and productivity in Latin America.

Beyond adoption and individual uses, the link of internet on productivity is expected to be related also to the intensity of its use. Different authors have intended to measure indicators of ICT intensity in the past. Cirera et al (2016) builded an internet index as an average of the different uses at firm level available in their sample (whether a firm uses internet for internal communication, e-commerce, managing inventory, marketing or research). Galliano and Roux (2008) measured ICT intensity as an indicator built considering the percentage of employees using the internet or email at the firm. Bartelsman et al (2013) built an ICT indicator from the geometric mean of latent probability estimates for a series of indicators as access to mobile internet, e-commerce, sharing of electronic data, among others. Considering that, we will extend the analysis to consider measures of internet intensity. Table 2 provides the detail of the intensity indicators to be used.

We will build an Internet Intensity index from the quantity of internet uses performed by the firm (among those represented in Table 1), normalised in order for the index to take values from zero to one. Therefore, firms which do not conduct any of the possible internet uses, reach an intensity value of zero. On the contrary, firms performing all possible uses, reach an intensity level of one. This Intensity Index can be seen as a proxy for real intensity levels, although we must admit that it is an imperfect measure of intensity as long as there exist other uses than those surveyed in the sample. Another limitation is that, due to insufficient data, the index only takes 6 possible values, so is not fully continuous as it should be if perfect information were available. In any case, the analysis will be complemented with the use of binary variables that identify three categories based on the values of the index (low, high, and full internet intensity). For that purpose we will consider low-intensity as the baseline category, and will add the dummy variables representing high intensity levels (those enterprises which exhibit intensity index levels above the mean,[9] but do not perform all possible uses) and full intensity levels, for the case of firms conducting all possible uses (intensity index=1).

[9] Bartelsman et al (2013) define a threshold of 0.6 to differentiate low and high intensity, which was found to be insufficient in our case, as it is considerably below the mean of our index (0.72).

3.3 The measure of Total Factor Productivity

To measure the effect of internet adoption and its use on the firm's productivity, we need to compute a suitable measure of the level of productivity of the firm. There is now wide consensus that the most appropriate one is that of the firm's TFP. Accordingly, we will compute the TFP level for each firm in the sample based on the estimation of the production function. In doing so, different approaches suggested in the literature were considered: Ordinary Least Squares (OLS), Fixed Effects (FE), and the methods proposed by Olley-Pakes (OP) and Levinsohn-Petrin (LP). It has been argued that OLS provide biased estimates because it does not consider the correlation between unobservable productivity shocks and input levels. The FE estimator solves the problem only if the unobserved firm-specific productivity is time-invariant. Olley and Pakes (1996) develop an estimator using investment as a proxy for these unobservable shocks. More recently, Levinsohn and Petrin (2003) argued about the problems related to investment as proxy, as it will not respond so smoothly to shocks, and proposed instead an estimator using intermediate inputs as proxies.

In brief, a firm-level Cobb-Douglas production function is specified:

$$log(VA)_{it} = \beta_0 + \beta_L log(L)_{it} + \beta_K log(K)_{it} + \omega_{it} + \eta_{it} \qquad [1]$$

where the variables are defined as in Table 3, and ω_{it} is the transmitted productivity component part of the error term, which can be expressed as a function of two observed inputs, capital and intermediates: $\omega_{it} = \omega_{it}(K_{it}, M_{it})$. As usual, the TFP level for each firm is estimated as a residual using a consistent estimation of the unknown parameters of [1].

It is worth to mention that before computing the TFP, a process of data cleaning was conducted in order to remove "nonsense" observations, which is close to the criteria followed by Ornaghi (2006). Firstly, we remove observations with negative value added. Secondly, we remove observations where the share of labour input is higher than 0.95 or lower than 0.05. Thirdly, we remove observations where the share of the sum of intermediate inputs *(M+E+F)* is higher than 0.95 or lower than 0.05. At the end, we obtain an unbalanced panel (2006 and 2010) of 7799 observations.

Other authors have estimated the firm's TFP using the WBES. Saliola and Seker (2011), using cross-section data for worldwide firms, estimated TFP series separately for each country, as the residual of the production function that included 2-digit industry fixed effects. In a study of the effects of competition on firm productivity for some countries of Central Asia and East Europe, Schiffbauer and Ospina (2010) estimated TFP following the method in Olley and Pakes (1996). Finally, González-Velosa et al (2016) applied the Levinsohn and Petrin (2003) procedure using data for a Latin American sample of firms from the WBES.

Tables A.1 and A.2 in Appendix summarize the main comparisons performed among the estimates based on OLS, FE, OP and LP. After an exhaustive analysis, the LP method was chosen as the preferred approach as it controls for simultaneity while using as proxy intermediate inputs that adjust more smoothly to shocks than investment. In any case, it should be mentioned that in order to reduce the impact of any potential bias, we will be computing the TFP by means of sector-specific estimates of the production function in [1] . Sector classification considered for TFP computation was defined following the Intermediate-level SNA/ISIC aggregation criteria. Table A.3 in Appendix summarizes the sectoral classification, which exhibit important differences in *K/L* and *Y/K* ratios, making worth the effort of performing sector-specific estimations.

The estimation of the production function parameters was performed using panel data observations for 2006 and 2010. Then, the TFP was computed for all firms, including those with only 2010 data available, using the estimated parameters. Equation [1] was estimated at a sectoral level when there were enough observations for doing so (sectors with aggregation code 4, 5, 6, 10, 11, 13, 14, 15 in Table A.3 in Appendix). In each case, TFP values were computed after estimation. For sectors with insufficient observations for the LP estimation, the procedure was modified as follows: (i) estimation of [1] for the complete sample, (ii) use this estimation to predict TFP only for sectors with insufficient observations.

3.4 Control variables

In order to assess properly the effect of internet on TFP we should control for a comprehensive set of firm characteristics. Otherwise, its effect may be confounded with that of some productive features of the firm, as long as they correlate with the adoption and use of internet. For that reason, we have revised extensively the literature to find out which sources of firm-level characteristics may explain differences in their productivity. Therefore, the control list was determined to be sufficiently exhaustive in order to pick all possible heterogeneity sources which may be affecting the relationship between internet and TFP. The chosen controls are expected to capture, even indirectly, the effect of most unobservables which may bias the estimation of the internet impact. Table 4 summarizes the control variables which will be considered.

In the first place, the analysis controls for the effect of innovation on productivity, through the development of new processes, which are expected to increase efficiency at the firm level. On the other hand, the effect of human capital on productivity is accounted for by the share of skilled workers over the total firm workforce. Knowledge stock and skills also constitute determinants of absorptive capacity, which may influence firm capabilities to make the most of new technologies (Benhabib and Spiegel, 1994; Cohen and Levinthal, 1990). Managerial talent may also constitute a source of firm performance (Gennaioli et al, 2013). While there is no data availability of the manager's education level in the Latin American module of the WBES, we will include as a proxy her/his experience in the sector. We will also consider the age of the firm to proxy its technological experience. The role of firm age is not theoretically straightforward. In fact, on the one hand, older firms are supposedly better equipped to assess the risks and benefits of the introduction of new technologies, which in turn should increase productivity; but on the other hand, younger enterprises are supposed to be more flexible to organizational changes which may also have an incidence on firm performance. Literature on productivity at firm level considers size as a main source of heterogeneity of firm's performance. Past research has found that big companies can amortize sunk costs, present more capacity for risk diversification, and have lower financial constraints (see for example Acs and Audretsch, 1988; or Cohen and Klepper, 1996). As a result, large firms are expected to be more productive than small ones. Castany et al (2005) argue that this may respond to the scale economies effect, the scope economies effect, the experience effect and organization effect. International links of the company can also have an incidence on firm performance. In fact, it is possible that companies exposed to international markets face a stronger pressure to innovate, in order to remain competitive. If exporter firms benefit from the technical expertise and best practices of their buyers, then some part of the efficiency of export-led firms may be attributed to externalities derived from exporting activity -*learning by exporting*- (Evenson and Westphal, 1995; Clerides et al, 1998). In the past, empirical studies have found that exporting firms are more efficient than their domestically oriented counterparts (Bernard and Jensen, 1995). R&D spillovers of trade partners may also become a source of productivity increases (see for instance Coe and Helpman, 1995, for a country level analysis, or Higon, 2007, for firm level evidence). On the other hand, Foreign Direct Investment (FDI) may also constitute a channel for international knowledge spillovers, if the organizational structure and governance of the multinational companies allow it. In particular, Glass and Saggi (1988) stipulate that openness can benefit technological development because local players can have access to new knowledge, technologies, and competencies from more advanced countries. Chou et al (2008), for instance, specifies a model, which includes FDI to explain productivity. Additionally, the fact that a firm is located in an urban or densely populated area can contribute to generate agglomeration economies, which may have an impact on firm performance. Country and industry dummies will also be considered, to account for national and sectoral fixed effects.

Finally, it is important to mention that the sample we will use to perform our empirical analysis presents some missing data, mainly due to non-replies on specific questions. However, and although the sample which will be effectively available to perform the estimations is smaller than the complete one, its characteristics seem to be quite similar, so sample selection should not be a cause of concern in our empirical analysis.[10]

4. Descriptive Analysis

Table 5 summarizes the descriptive statistics for the internet-related variables. As it can be seen, there is a high level of internet adoption (88%), while the less-intensive uses are close to universal (e.g. email use of 92%). However, figures are considerably reduced when we further analyze the data available for more sophisticated activities. For instance, only 62% of the firms in the sample use an own website. To have a higher proportion of email users than internet adoption should not be surprising, as there could still be some firms with slow dial-up internet connections in 2010, which do not classify as broadband, but still can be used for sending and receiving emails. On the contrary, the fact that more than 70% of the firms declare to use internet for research

[10] Detail available upon request

activities seems to be suspiciously large, as is it well known that Latin America lags behind most regions in innovation activity. Therefore, results should be taken with caution, as some variables are based on the respondent perception, so measurement errors should not be discarded.

As for the intensity values, 26% of the firms are classified as high-intensive, while 36% reach full intensity levels. The fact that 62% of the firms are supposed to reach intensity levels above the mean may also seem to be too optimistic, reflecting the limitations of the data available, and making worth the distinction between high and full intensity.

There is likely to be some overlapping information in the measures of internet described in Table 1. For instance, internet uses are not only non-excludable, but also closely related to each other as well. This will be important to consider in the econometric estimations to be performed, as introducing many of the variables as regressors at the same time may generate collinearity problems, preventing the precise identification of the corresponding effects. The correlation coefficients between the internet indicators reported in Table 6 allows to make an assessment of this concern. They confirm the association between the different measures. Internet adoption is clearly correlated with all possible uses (except email, it is almost impossible to perform those uses without a broadband connection), while the internet use for purchases also seems to be closely correlated with using it to deliver services or performing research activities. In any case, figures in Table 6 suggest that each particular measure contains specific sources of information, as the level of association between any pair of indicators seems to be far from perfect.

Intending to begin testing our first two hypotheses we will start in finding whether there are differences in the firm's log(TFP) under different scenarios of internet adoption and use. Table 7 summarize the results for firms having internet adoption or not, and depending on the different categories of internet use and intensity. As expected, those firms which have adopted or used internet are linked to higher productivity levels. This seems to be particularly pronounced in the case of internet adoption, email and website use, and to a less degree, to the remaining uses. For all cases, the mean difference test confirms clearly that productivity associated to those firms which have adopted or used internet is higher. Similarly, the comparison of the

TFP levels in the group of firms that uses very intensively internet with the one that does it moderately or not at all can be used as an initial assessment of the second hypothesis of this study, as results suggest that the higher the intensity, the larger the mean of log(TFP).

Finally, in order to get some initial insights about our third hypothesis, we have computed the density functions of the distribution of the log(TFP) for firms adopting or using internet with those that do not, as well as the log(TFP) associated to different quantiles of the distribution in the two groups of firms. The comparison of the densities is made in the graphs in Figures 1 and 2, whereas that of the TFP levels at the selected quantiles are reported in Table 8.

Clearly, enterprises with advanced levels of internet availability or use have productivity distributions which dominate those which do not (densities for the former group of firms are at the right of the latter group). This is verified for all different samples that exhibit internet features in comparison with those which do not, although it seems to be especially pronounced for the case of internet adoption, website and email use. In all cases, formal Kolmogorov-Smirnov tests for equality of distribution functions were conducted, with results confirming different TFP distributions for the respective groups of firms.[11] This results have implications for the analysis, as they provide clear evidence that firms adopting and making use of internet are more productive. Interestingly, it also suggests that the effect of internet on TFP could be far from homogeneous as it seems to vary depending on the position of the firm in the productivity distribution.

Overall, the descriptive analysis is consistent with the hypotheses in this paper, although more analysis is required before reaching a solid conclusion. To be clear, the observed association, at the mean and in different parts of the TFP distribution, between the internet indicators and the level of firm's TFP could be explained by other characteristics that affect both productivity and internet adoption and use. Therefore, the precise measure of the effect of internet should be estimated conditioned to the set of these other firm characteristics.

[11] Detail available upon request

5. Model specification

In this section, we outline the model to empirically study the link between internet and firm productivity in firms in Latin America. We will follow a similar specification as other articles in the literature (Castany et al, 2005; De Stefano et al, 2016; González-Velosa et al, 2016), using the estimated measure of TFP (in logs) as the dependent variable and considering the set of variables related to internet adoption and use, and the firm controls introduced in section 3 (see Tables 1, 2 and 4):

$$log(TFP_i) = \beta_0 + \beta_1 INTERNET_i + \beta_2 INNOV_i + \beta_3 HK_i + \beta_4 MANAGER\_EXP_i + \beta_5 AGE_i + \beta_6 SIZE_i + \beta_7 EXPORT_i + \beta_8 FDI_i + \beta_9 LOCATION_i + \beta_{10} IND_i + \beta_{11} COUNTRY_i + \mu_i \qquad [2]$$

where μ_i is a well-behaved error term for firm *i*.

As stated before, possible endogeneity of the measures of internet is a potential cause of concern in the estimation of equation [2].[12] Endogeneity can arise as a result of different reasons. On the one hand, omitted internal to the firm factors which can have an incidence in TFP and at the same time be related to the internet variables, as managerial talent or organizational capital for which we have no data available (as stated before, we can proxy managerial talent only through the manager experience due to the lack of data on the manager education in the sample of Latin American firms). As a positive relationship is expected between those unobservables with TFP and internet, the OLS estimation of the effect of internet will be upwardly biased. Another potential source of endogeneity is simultaneity. A common critique in this type of studies is that the estimated effect of ICT and broadband is just capturing the correlation with the firm's productivity from which a causality effect should not be inferred. The reason is that investment in ICT may be considered as a driver of productivity, but also react to changes in productivity (Cardona et al, 2013). This reverse causality arise because most-productive firms would have higher resources to face the costs associated to ICTs. As a result, the OLS estimated parameter would be

[12] It should be mentioned that endogeneity is not treated or even discussed in some previous similar studies in the literature. For instance, in their recent study Paunov and Rollo (2016) instrumented the industry adoption internet rates but did not consider an issue the endogeneity of the firm-level internet use.

capturing also the effect going from productivity to ICT. Finally, another source of endogeneity can be the existence of measurement errors. Examples of this can be misreporting, or internet indicators that do not fully capture its real using levels by the firm. In this case, we can expect an attenuation bias in the OLS coefficients of the internet measures, capturing a lower than expected impact of internet on productivity.

Different actions have been carried out to tackle the issue of endogeneity of the measures of ICT. In the first place, a comprehensive list of controls for observable characteristics that are known to affect the firm's level of productivity has been included in [2]. This is crucial due to the impossibility to directly control for firm unobservable characteristics in a cross-section setting. Besides accounting for the direct effect of these characteristics and for differences across industries and countries, they may well capture a big deal of the effect of most of the unobservables that could distort the estimation of the effect of internet on productivity. For instance, as long as innovation is affected by managerial talent, the inclusion of the former variable would be capturing in an indirect manner the effect on productivity of the latter. As a result, the pernicious impact of the omission of managerial talent in [2] on the estimated effect of internet is expected to be much lower. Similarly, FDI may also include the effect of other unobservables, as foreign enterprises are usually expected to adopt better organizational practices and to the capacity of firms to compete in international markets. In addition, we have obtained estimates substituting the contemporaneous measures of internet -when available- by their corresponding lagged values, to assess the effect that simultaneity could have on the estimated effect of internet. This is a procedure used frequently in the extant literature to mitigate the problem of endogeneity due to simultaneity. Finally, the parameters in [2] have been estimated by the instrumental variables (IV) method. As usual in these situations, the major challenge is to find suitable instruments for the measures of internet. In any case, the aim of this part of the study will be to obtain the most robust empirical evidence possible to test our first two hypotheses.

In order to be able to test the third hypothesis, referred to analyze possible differences in the link between internet and TFP along the productivity distribution, we need to follow a different approach, as the methods mentioned so far only provide estimates of the coefficients at the mean. Through the descriptive analysis some insights suggested the presence of this heterogeneous link, although a more robust approach was needed in order to obtain clearer evidence. To take into account this kind of heterogeneities, the framework that has prevaded in applied economics is the CQR approach developed by Koenker and Bassett (1978), which has been used, for example, by Paunov and Rollo (2016) in their study of the effect of the industry's adoption of internet on the firm's productivity and innovation performance. The CQR estimations refer to specific points in the conditional productivity distribution, where all individuals are assumed to have the same observed characteristics, meaning that they do not correspond to the impact on the overall productivity distribution of the Latin American firms. In other words, CQR provides the estimated impact of a covariate on a quantile of the productivity conditional on specific values of the other covariates. As a result of that, CQR generate results that may not be generalizable or interpretable in a policy or population context. Conversely, the UQR provides more interpretable results as it marginalizes the effect over the distributions of the other covariates in the model. As a result, in contrast with the CQR, the UQR is more appropriate when the ultimate object of interest is the effect on the unconditional distribution. In the case under study, the unconditional second decile refers to low productive firms, whereas the conditional second decile refers to low productive firms conditional to the set of firm characteristics included as covariates in the specification, firms that however may not necessarily be low productive overall. Therefore, as we are especially concerned with the effect of increasing the internet adoption and use on the unconditional productivity distribution and, more precisely, on the amount of inequality in this distribution, the UQR is far more suitable to test our hypothesis.

Among the methods proposed so far to implement the UQR, we choose that proposed by Firpo et al (2009) due to its easy of computation (other alternatives include the methods by Rothe, 2010 and Frölich and Melly, 2013). The procedure by Firpo et al (2009) consists of running a regression of a transformation —a (recentered) influence function— of the outcome variable on the explanatory variables. The influence function *IF(Y; vFY)* of a distributional statistic *v(FY)* represents the influence of an individual observation on that distributional statistic. Adding back the statistic *v(FY)* to the influence function yields what the authors call as "recentered influence function" (*RIF*). As a result, the dependent variable in the regression is the *RIF*, and a simple OLS regression of this new dependent variable can be run on the covariates.

6. Results

6.1 Effects at the mean of the productivity distribution

Table 9 summarizes results of the OLS estimation of equation [2], using each of the available indicators of internet adoption and use introduced in section 3. Internet adoption seems to be related to an 11% increase in TFP in Latin American firms. In other words, firms that adopted internet are 11% more productive than similar firms that did not. The available internet-related uses exert also a significantly positive effect, with the only exception of performing research activities. The insignificance of the coefficient associated to using internet for research may be due to the fact that this kind of activities may not reach immediate effects, possibly because it takes some time to translate research into innovations and eventually to productivity gains. Another possible reason is measurement error in this variable because, as shown in the descriptive analysis, an unexpected high proportion of firms declared to use internet for research. Beyond that, there seem to be differences in the magnitude of the effect for the other internet use variables. For instance, while using an own website seems to be related with a 20% increase in TFP (significant at 1%), using internet for delivering services "only" seems to increase TFP by 8% (significant at 5%). Further estimations (columns (iv) and (viii) in Table 9) were considered for specifications that include more than one internet-use variables at a time. To minimize collinearity among the internet indicators, and taking into account the distinction between input- and output-based measures, we group them in two categories: those corresponding to "inputs" or "use channels", as email and having an own website, and those proxying for final uses or "outputs", as making purchases, delivering services, and performing research activities. Adding together website and email (column (iv) in Table 9) keep unchanged the coefficient and significance level for the first variable, whilst the effect for the email appears to vanish. This seems to confirm a strong link between having a website and productivity, helping the firms in its diffusion activities and improving the communication channels with potential clients and suppliers. In contrast, there does not seem to be any productivity gain for firms using email once controlling for having a website. Regarding results for the specifications that include all the indicators of final uses, results in column (viii) of Table 9 shows that their estimated effects are reduced. In fact, only the effect of internet use for purchases remains as strongly statistically significant, while that for deliver services is marginally significant (at

10%) and reduces its magnitude substantially with respect the specification that includes only this use of internet (column (vi)). In order to verify the robustness of these results, additional contrasts were conducted after estimation, verifying the joint significance for all internet uses.

Finally, the last two columns in Table 9 summarise results obtained when using the internet intensity variables, which synthesizes the information contained in all the internet measures. In column (ix), this index is included as a continuous regressor, whereas the results for the three categories defined based on the value of the index (low, high, and full internet intensity) are shown in column (x). Results are very clear in the sense that, as hypothesized, a higher intensity of use is linked to more productive firms. An increase of one standard deviation in the intensity index raises 0.013% the level of TFP, an estimated effect that is highly significant. Similarly, results in column (x) for the dummy variables denoting firms with high and full intensive uses of internet confirm the productivity-enhancing effect of using internet intensively: the TFP level of firms with a high intensive use is about 7 percentage points higher than otherwise similar firms that make a low use. The gap increases even further for firms that perform all possible uses, up to 14 percentage points. This is reasonable in the sense that internet connectivity does not guarantee productivity gains per se, but only if used in activities that allow the firm to reduce production and distribution costs, improve the management and control of the different processes, increase the amount of relevant information, and the like. The positive and significant coefficients of these intensity indicators confirm the importance of simultaneously using internet in various aspects of business activity in order to obtain productivity gains. The combined use of internet for different activities seems to be relevant beyond the individual uses. Overall, these results seem to confirm that simple access to technology is not sufficient to obtain a performance improvement, instead using it adequately is necessary in order to fully exploit its potential. Therefore, this evidence supports our second hypothesis.

Although they are not the main focus of the analysis in this paper, it is worth mentioning that the estimated effect of all the firm characteristics included in the model as control variables is in line with that expected on a priori grounds and consistent with what has been reported in the previous literature. Firm size is positively associated with productivity, as the coefficients for the micro, small and medium sized firms are, in all cases, significantly negative (the omitted category is large firms). One controlling by size, the productivity of the Latin American firms increase with their age in a quite robust manner. There is also a significant positive association with productivity of human capital and internationalization, both in terms of FDI and export activity. The estimated effect of innovation is also positive although it is only marginally significant in some specifications, whereas the manager's experience does not seem to affect the level of productivity once the other sources of heterogeneity have been taken into account. On the other hand, estimates for the coefficients of the location variables support somehow the existence of benefits linked to agglomeration/urbanization economies, despite some of the estimated effects are only marginally significant, and that firms in small cities have on average similar levels of productivity to those in big cities, and even in capital cities. Finally, the significance of the industry and country fixed effects confirms[13] the existence of differences between firms in different sectors of activity and in different countries.

However, as discussed before, the OLS method is likely to provide biased estimates of the causal effect of internet if the variables proxying for this factor are endogenous. As discussed in section 5, the comprehensive list of observable characteristics included in the specifications used to estimate the effect of internet should, hopefully, mitigate the pernicious effect of endogeneity. Still, as a sort of robustness check, we have considered all the possibilities at hand to address this issue. In the first place, we took advantage of the fact that the Latin America 2006 wave of the WBES included information about two of the internet related variables: email and website. As a result, we were able to replace the contemporaneous values for these measures with the values reported in 2006, for a subsample of enterprises. Using lagged values of the firm characteristics has been common practice in the literature related, for instance, to innovation (Seker, 2012). Due to data limitations, only 606 enterprises could be considered in this analysis, which is exposed in detail in Table A.4 in Appendix. Parameters estimated using the contemporaneous values (observed in 2010) and those reported in 2006 seem to be close in comparison, which suggests that any estimation bias using the contemporaneous data seems to be limited. It is worth noting that this argument would be valid only under the assumption of far from perfect persistence in

[13] Joint significance tests were conducted respectively to sectoral and country variables in order to confirm this assertion.

the measures of internet. In other words, when there is not high correlation between the values observed in 2010 and 2006, which seems to be the case in our exercise (correlation for email is 0.310 and for website 0.394). It is also worth to mention that the characteristics of the subsample for which this check was implemented are roughly similar to the full one, implying that sample selection is not a concern.[14] With due caution, our reading of these results is that the OLS estimates discussed above should not be strongly affected by reverse causality.

Regarding the implementation of the IV estimator, as was already mentioned in section 5 it has been quite challenging to find suitable instruments for the measures of the firm's adoption and use of internet. Highly conditioned by the availability of information in the WBES dataset, we have considered different sets of variables as instruments. In the first place, the 4-year lagged values of the email and website indicators for the subsample of firms for which they are available. As indicated above, these lagged indicators correlate with the contemporaneous measures and are supposed not to affect directly the current level of productivity once the contemporaneous values are included in the model. Secondly, we have computed a set of instruments by interacting country-level telecom indicators measured a decade ago (fixed telephone lines and internet users every 100 inhabitants, with a 10-year lag) with the firm age and size (further details on these instruments are provided in Appendix). The idea behind these instruments is that higher adoption and use is expected for firms in environments that are more prone to the telecom technology. It is also assumed that this effect of the environment is likely to vary within each country depending on the age and size of the firms. In brief, the internet adoption and use by firms observed in 2010 are supposed to correlate with the penetration of the telecom technologies in the country ten years before, with differences across firms depending on the age and size. On the other hand, it is assumed that these aggregate measures do not correlate with the shocks that affect the productivity of single firms (error term in equation [2]).

All the IV estimations using these instruments were performed following the limited-information maximum likelihood (IV-LIML) procedure, which has proven to be more suitable than the Two-Stage Least Squares in the presence of weak instruments (coefficients and standard deviations estimated through IV-LIML should

[14] Detail available upon request

be less affected by the weakness of the instruments). Instruments based on lagged email and website variables were found to be strong, but presented concerns in terms of the compliance of exclusion restrictions. On the other hand, country-level instruments seem to verify clearly with exclusion restrictions, but seemed to be significantly weaker. Results are exposed in detail in Tables A.6 to A.8 in Appendix, suggesting that the effect of internet adoption and use on TFP could be higher than those suggested by the OLS estimations. Therefore, with due caution due to the concerns about the suitability of the instruments, we can consider the OLS estimated coefficients to represent a lower-bound of the causal effect of internet on TFP.

6.2 Effects along the productivity distribution

In order to test our third hypothesis, i.e. the heterogenous effect of internet along the productivity distribution and, consequently, the impact that the increase in the internet adoption and use could have on productivity inequality among Latin American firms, we extend the analysis to consider results from UQR. Before discussing the results, two comments are in order. The first one has to do with the interpretation of the estimated effects in this case. As mentioned in section 5, UQR allow estimating the impact of a change in the characteristic of interest on each quantile of the overall distribution. Adapting the argument in Fournier and Koske (2012) to the case of this study, they allow estimating the effect on the level of productivity of a particular quantile of increasing by 1 percentage point the share of firms using internet, holding the other firm characteristics constant. In addition, implications for the impact on the amount of inequality in the productivity distribution can be inferred from the profile of the estimated effect. A downward sloping trend in the effect over the quantiles should be read as a higher increase in productivity for the less productive firm induced by the raise in the share of firms using internet and, thus, that extending the use of this technology will contribute to decrease inequality in productivity. Conversely, an increasing effect along the distribution will be observed when extending internet among the Latin American firms contribute to exacerbate productivity inequality. The second comment refers to the endogeneity of the measures of internet in the context of the UQR. The method by Firpo et al (2009) results in appropriate estimates of the effect of interest if there is not unobserved heterogeneity or if the unobserved characteristics are independent of the observed ones, and provided there is not reverse causality. As discussed in the case of the estimates in the average, endogeneity of the variable of interest in this study is a reasonable concern as these assumption probably do not hold. However, besides the challenge of finding suitable instruments, in the framework of the UQR there is not, as far as we are aware, a general procedure to account for endogeneity. Frölich and Melly (2013) suggested a method but only when the endogenous treatment variable is instrumented by a single binary variable, which in our opinion is not convenient due to the characteristics of our specification and the instruments available. In any case, as stressed by Fournier and Koske (2012), the comparison between the estimates for the different quantiles would still be valid if the bias is homogeneous over the distribution (i.e. endogeneity does not affect differently the estimate of the effect at different quantiles). In any case, as for the estimates in the average, implications in terms of causality should be derived with caution, and we will take the estimated effects from the UQR as a lower-bound of the impact of internet in the different parts of the distribution. In this regard, it should be mentioned that Paunov and Rollo (2016), which is the closest article to ours in terms of contents and data used, also consider the enterprise internet variables to be exogenous in their quantile regression estimates.

The unconditional effect of the different measures of internet has been estimated at different points of the log(TFP) distribution. Figure 3 summarizes the estimated coefficients, for each internet variable, along with their respective 95% confidence intervals (further details are provided in Table A.9 in Appendix). For instance, it can be observed that if the percentage of firms adopting internet increases in 10 percentage points, the TFP at the second decile will increase by 2.2%, 1.6% at the median, while TFP on the seventh decile will only increase by 1%. In most cases, the effect at the median seems to be close as that of the mean, with higher values at the left of the distribution and lower at the right. The highest coefficients are reached in most cases at the second decile, after which the coefficients start to decrease consistently to become negligible in most cases at the right-end of the productivity distribution.

This is consistent with a situation in which enterprises with lower levels of productivity are able to yield bigger gains as a results of the extension in the use of internet than more productive firms, as are playing catch-up, with higher potential to grow as are starting from behind. As stated before, firms that are lagging behind surely faced important constraints in comparison to the most advanced ones, as having lower access to *offline* knowledge networks, and facing bigger difficulties to enlarge its interactions with clients and suppliers, as well as facing other restrictions derived from its environment. By adopting and using internet, those difficulties may be partially reverted, yielding as a result productivity performance gains that are comparatively larger than those of more productive firms. The economic implications in this case suggest that internet adoption and use may contribute to decrease TFP differences between enterprises in the long term –promoting a level playing field–, as inequalities on TFP distribution seem to be reduced. Similar conclusions can be made with most of the alternative internet uses (email use, internet used for purchases, internet for deliver services, and internet used for research), as the impact on productivity of increasing the share of firms making these uses seem to be much higher at lower quantiles of the productivity distribution. In the case of using an own website, the effect is higher for less productive firms, as the coefficient evidences decreasing results from the median, although it increases for most productive firms. This should be explained by the fact that it is possible that having an own website presents the potential for higher productivity gains if used intensively, something than only the more productive firms should have the resources to fully exploit. For instance, most productive firms may have more developed websites, which could be used as platforms for e-commerce and interaction with customers, in contrast with more disadvantaged firms that may have more primitive sites. Moreover, the possibility of registering clients in the firm's website creates the opportunity of collect, store and manipulate massive data from customers, –the so called big data– which provides very useful statistical reports and predictive models for business analysis that can give key information to the firms, in order to understand the necessities of its clients, design better offers, and conduct more sophisticated diffusion and marketing activities. This kind of tasks are well beyond the capabilities of smaller or less productive firms.

Beyond individual internet adoption and use, intensity levels were also tested through the UQR approach. As can be seen, in this case also the highest coefficients are reached at the lower end of the distribution, decreasing from that point. However, significant and positive coefficients are still reached at some upper deciles, meaning that extending the intensive use of internet seems to also provide higher returns for firms with high levels of productivity.

Overall, the downward-sloping trend over the TFP distribution of the effect of increasing the share of firms using internet, and doing it intensively, provides support to the third hypothesis of this paper. That is to say, the evidence suggest that extending the use of these ICT technologies among Latin American firms contributes to reduce inequality in productivity levels. This is a result that, as far as we are aware, has not been reported in the extant literature neither for the Latin America region nor for any other developed or developing economy or group of economies.

7. Final remarks

To summarize, this paper contributes to the empirical literature by exploring the link between internet and productivity in Latin American firms. Through our empirical analysis, we found robust empirical evidence on the positive relationship between internet and firm-performance. In particular, internet adoption and use seem to constitute a source of productivity growth for Latin American firms. Secondly, higher intensity of internet use in firms seems to be linked with bigger productivity gains. These results seem to prove our two first hypotheses, and are aligned with previous ICT literature in the developed world, which suggests that internet plays an important role as innovation enabler and productivity enhancer. In third place, and providing novel evidence in the literature, low-medium productive firms seem to benefit more from internet adoption and use, in comparison with those with higher productivity levels, verifying our third hypothesis that the impact of the new technologies on productivity levels do not seem to be uniform for all enterprises. In fact, it seems that internet adoption contributes to decrease TFP differences between enterprises, as inequalities on its distribution seem to be reduced.

The availability of this new empirical evidence specific for Latin America may offer useful insights to policymakers for the design and implementation of initiatives aimed at fostering productivity by increasing broadband connectivity. From a policy perspective, the evidence found in this article supports the initiatives that have been promoting most Latin American governments, as Digital Agendas and National Broadband plans, as well as the effort being made by the telecommunications industry, under the form of investments for network deployments. In the case of governments, promoting internet adoption and use at firm levels may be seen as a tool to reduce disparities among enterprises, promoting a level playing field, something which is especially relevant for Latin America, as one of the most unequal regions in the world. From a long-term perspective, these results can potentially suggest very important consequences for Latin America.

However, our analysis has been limited by two main reasons. In first place, while we were able to perform robustness analysis controlling endogeneity in estimations at the mean, it has not been possible to extend those controls to the UQR analysis. For that reason, causality implications of our UQR analysis must be taken with caution, and will have to be further addressed in future research. In second place, limitations on data availability prevented us to make a much richer analysis. Future research should intend to find out why some firms are able to extract more productivity gains from technology in comparison with others. Also, further research may also look at the role of the national ICT industry. For example, the possibility of a country to produce software adapted to the needs of local firms may play a role not only in ICTs adoption decisions, but also in the impact of ICTs on the firm performance, once adopted. These extensions may provide a deeper understanding of the linkages between ICTs and firm performance, and on the characteristics that effective public policies should have.

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Table 1: Internet related variables

Variable	Question in survey	Possible answers
Internet adoption	Does this establishment have a high-speed Internet connection on its premises?	Yes/No/Don't know (spontaneous)
Email	At the present time, does this establishment use Email to communicate with clients or suppliers?	Yes/No/Don't know (spontaneous)
Website	At the present time, does this establishment use its own website?	Yes/No/Don't know (spontaneous)
Internet use for purchases	Is this establishment's Internet connection used to Make purchases for this establishment?	Yes/No/Don't Know (spontaneous)/NA (spontaneous)
Internet for delivering services	Is this establishment's Internet connection used to Deliver services to this establishment's clients?	Yes/No/Don't Know (spontaneous)/NA (spontaneous)
Internet use for research	Is this establishment's Internet connection used to Do research and develop ideas on new products and services?	Yes/No/Don't Know (spontaneous)/NA (spontaneous)

Source: authors own elaboration

Table 2: Internet Intensity variables

Variable	Description
Internet Intensity Index	Quantity of internet uses conducted by the firm (website, email, internet use for purchases, internet for delivering services, internet use for research), divided by all possible uses (5)
Low Internet Intensity	Dummy variable which takes the value of 1 if the Internet Intensity Index for the firm is lower than the sample mean of the Index.
High Internet Intensity	Dummy variable which takes the value of 1 if Internet Intensity Index for the firm is above the sample mean of the Index but less than 1.
Full Internet Intensity	Dummy variable which takes the value of 1 if the firm perform all possible internet uses (Internet Intensity Index = 1)

Source: authors own elaboration

Table 3: Variables used for TFP estimation

Variable	Code	Description
Output	Y	Total sales, last fiscal year
Physical Capital	K	Cost to repurchase all machinery
Labour	L	Total labour costs, last year
Materials	M	Total cost of raw materials and intermediate goods, last fiscal year
Electricity	E	Total cost of electricity, last fiscal year
Fuel	F	Total cost of fuel, last fiscal year
Value Added	VA	$Y - M - E - F$

Source: authors own elaboration

Table 4: Control variables

Variable	Code	Description
Innovation	*INNOV*	Dummy variable for firms that introduced a new or significantly improved process for producing or supplying products over the last 3 years.
Human Capital	*HK*	Percentage of workers with at least a bachelor's degree
Manager Experience	*MANAGER_EXP*	Experience of the top manager at the firm sector (years)
Age	*AGE*	Age of the firm (years)
Size	*SIZE*	Dummy variables: *Micro* (10 or less employees); *Small* (11-50 employees); *Medium* (51-250 employees); *Large* (baseline scenario, 251 or more employees).
Export activity	*EXPORT*	Dummy variable if 10% or more of the firm sales are exported
Foreign investment	*FDI*	Dummy variables if at least 10% of the capital is foreign owned.
Location effects	*LOCATION*	Dummy variables, representing capital cities (*Capital city*), other cities with over 1 million people (*Big city*), cities with 250.000—1 million people (*Medium city*), and cities with 50.000-250.000 people (*Small city*)
Industry effects	*IND*	2-digit sector dummy variables
Country effects	*COUNTRY*	Country dummy variables

Source: authors own elaboration

Table 5: Descriptive statistics of internet indicators (2010)

Variable	Proportion/Mean	Standard Error	Observations
Internet adoption	0.878	0.005	4151
Website	0.623	0.007	4612
Email	0.922	0.004	4612
Internet use for purchases	0.659	0.007	4151
Internet to deliver services	0.643	0.007	4151
Internet use for research	0.709	0.007	4151
Internet Intensity Index	0.720	0.295	4147
High Internet Intensity	0.262	0.007	4147
Full Internet Intensity	0.361	0.007	4147

Source: authors own elaboration

Table 6: Correlation of internet-related variables (2010)

	Internet adoption	Website	Email	Internet use for purchases	Internet to deliver services	Internet use for research	Internet Intensity Index	High Internet Intensity	Full Internet Intensity
Internet adoption	1								
Website	0.351***	1							
Email	0.537***	0.330***	1						
Internet use for purchases	0.518***	0.288***	0.333***	1					
Internet to deliver services	0.501***	0.240***	0.315***	0.479***	1				
Internet use for research	0.582***	0.266***	0.344***	0.409***	0.375***	1			
Internet Intensity Index	0.714***	0.631***	0.593***	0.753***	0.726***	0.707***	1		
High Internet Intensity	0.223***	-0.026*	0.153***	0.198***	0.116***	0.136***	0.161***	1	
Full Internet Intensity	0.280***	0.540***	0.204***	0.540***	0.559***	0.481***	0.712***	-0.448***	1

*Source: authors own elaboration. *** denotes significance at 1% level*

Table 7: Differences in mean of log(TFP) depending on internet adoption and use.

Conditional		Mean log(TFP)	Std. Deviation log(TFP)	Observations	Mean-difference test
Internet adoption	*No*	2.694	0.789	440	-12.318***
	Yes	3.199	0.905	3239	
Website	*No*	2.780	0.789	1525	-19.161***
	Yes	3.298	0.906	2544	
Email	*No*	2.582	0.060	317	-12.553***
	Yes	3.147	0.897	3751	
Internet use for purchases	*No*	2.911	0.866	1249	-11.289***
	Yes	3.256	0.905	2430	
Internet to deliver services	*No*	2.955	0.878	1306	-9.304***
	Yes	3.240	0.906	2373	
Internet use for research	*No*	2.962	0.912	1062	-7.454***
	Yes	3.210	0.895	2617	
Internet Intensity	*Low*	2.907	0.867	1383	
	High	3.177	0.880	960	-7.373*** (a)
	Full	3.352	0.911	1332	-4.603*** (b)

Source: authors own elaboration. Note: In the mean difference tests, the null hypothesis refers to no difference in the mean of the two samples. (a) Mean comparison with respect to the sample of low intensity levels. (b) Mean comparison with respect to the sample of high intensity levels.

Table 8: Differences in distribution of log(TFP) depending on internet adoption and use.

		Quantile of log(TFP)				
		0.1	0.3	0.5	0.7	0.9
Internet adoption	*No*	1.866	2.327	2.642	3.013	3.640
	Yes	2.169	2.732	3.144	3.606	4.349
Website	*No*	1.916	2.378	2.713	3.133	3.787
	Yes	2.299	2.850	3.237	3.710	4.435
Email	*No*	1.830	2.262	2.511	2.797	3.419
	Yes	2.128	2.694	3.091	3.545	4.292
Internet use for purchases	*No*	1.965	2.460	2.820	3.318	4.031
	Yes	2.250	2.797	3.193	3.662	4.395
Internet to deliver services	*No*	1.964	2.508	2.902	3.364	4.121
	Yes	2.230	2.765	3.170	3.643	4.386
Internet use for research	*No*	1.942	2.508	2.879	3.398	4.131
	Yes	2.181	2.740	3.150	3.601	4.351
Internet Intensity	*Low*	1.940	2.465	2.828	3.317	4.025
	High	2.175	2.725	3.112	3.571	4.288
	Full	2.346	2.893	3.284	3.776	4.486

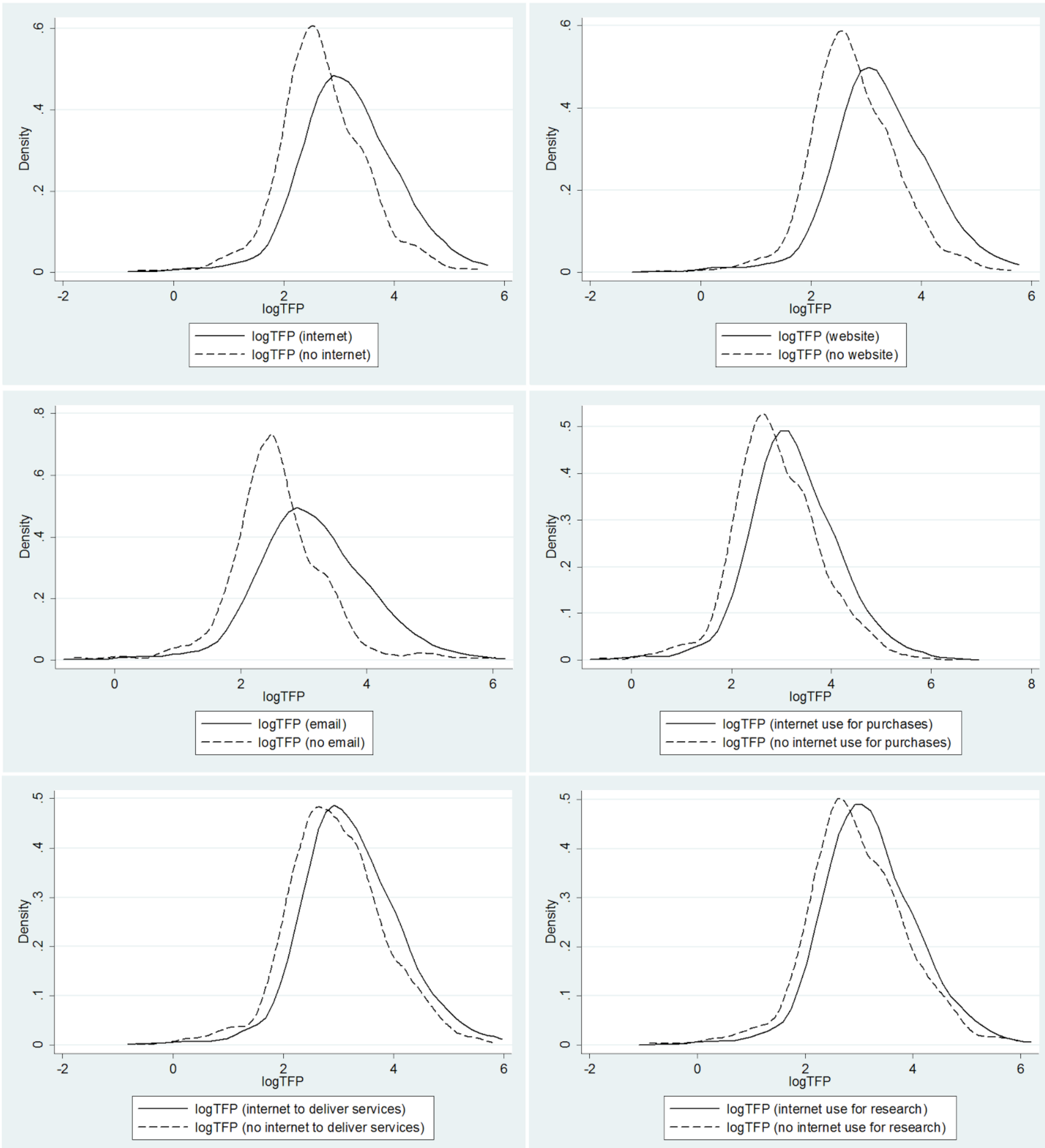
Source: authors own elaboration

Table 9: OLS estimations at the mean

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Internet adoption	0.110***									
	[0.029]									
Website		0.196***		0.192***						
		[0.026]		[0.026]						
Email			0.095**	0.044						
			[0.037]	[0.037]						
Internet used for purchases					0.102***			0.083***		
					[0.024]			[0.026]		
Internet for delivering services						0.076***		0.042*		
						[0.026]		[0.025]		
Internet used for research							0.047	0.003		
							[0.034]	[0.033]		
Internet intensity index									0.259***	
									[0.049]	
High Internet intensity										0.070**
										[0.035]
Full Internet intensity										0.141***
										[0.035]
Micro size	-0.920***	-0.853***	-0.937***	-0.848***	-0.916***	-0.935***	-0.935***	-0.914***	-0.875***	-0.901***
	[0.058]	[0.051]	[0.055]	[0.053]	[0.057]	[0.055]	[0.057]	[0.058]	[0.059]	[0.057]
Small size	-0.605***	-0.560***	-0.615***	-0.560***	-0.604***	-0.610***	-0.608***	-0.604***	-0.585***	-0.588***
	[0.049]	[0.046]	[0.048]	[0.046]	[0.048]	[0.048]	[0.049]	[0.048]	[0.048]	[0.048]
Medium size	-0.295***	-0.278***	-0.300***	-0.279***	-0.298***	-0.297***	-0.295***	-0.298***	-0.292***	-0.290***
	[0.043]	[0.041]	[0.042]	[0.041]	[0.043]	[0.043]	[0.043]	[0.044]	[0.044]	[0.043]
Human Capital	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Manager Experience	-0.001*	-0.001	-0.001*	-0.001	-0.001*	-0.001*	-0.001	-0.001*	-0.001	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Innovation	0.038**	0.033*	0.045**	0.032	0.034*	0.036*	0.037*	0.031	0.022	0.025
	[0.018]	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]	[0.020]	[0.020]	[0.020]
Age	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
FDI	0.142***	0.131***	0.125***	0.131***	0.144***	0.142***	0.144***	0.145***	0.150***	0.148***
	[0.032]	[0.027]	[0.029]	[0.027]	[0.031]	[0.031]	[0.031]	[0.031]	[0.031]	[0.031]
Export	0.102**	0.092***	0.107***	0.092***	0.102**	0.104**	0.104***	0.102**	0.096**	0.099**
	[0.041]	[0.034]	[0.035]	[0.034]	[0.040]	[0.041]	[0.040]	[0.041]	[0.040]	[0.040]
Capital City	0.119**	0.108**	0.112**	0.107**	0.122**	0.116**	0.120**	0.120**	0.116**	0.120**
	[0.053]	[0.049]	[0.052]	[0.050]	[0.052]	[0.052]	[0.052]	[0.052]	[0.053]	[0.051]
Big City	0.120*	0.116*	0.114**	0.115*	0.120*	0.119*	0.117*	0.120*	0.119*	0.118*
	[0.067]	[0.067]	[0.068]	[0.067]	[0.067]	[0.067]	[0.068]	[0.067]	[0.068]	[0.067]
Medium City	0.091	0.087	0.077	0.087	0.086	0.087	0.087	0.088	0.094	0.089
	[0.064]	[0.061]	[0.062]	[0.061]	[0.064]	[0.063]	[0.063]	[0.063]	[0.064]	[0.063]
Small City	0.119*	0.111**	0.110*	0.113**	0.123**	0.114*	0.119**	0.120*	0.124**	0.120**
	[0.061]	[0.056]	[0.057]	[0.056]	[0.061]	[0.060]	[0.061]	[0.061]	[0.061]	[0.060]
R-squared	0.533	0.548	0.541	0.548	0.534	0.533	0.532	0.535	0.537	0.535
Observations	3587	3963	3962	3962	3587	3587	3587	3587	3585	3585

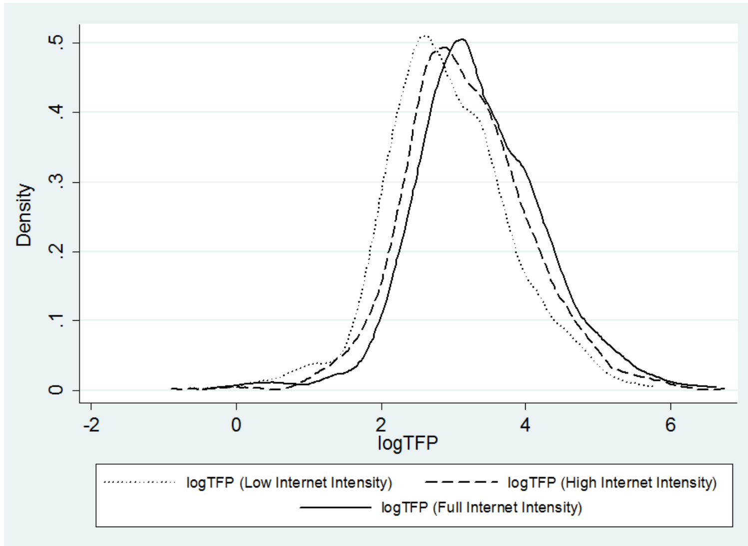
Source: authors own elaboration. Notes: Robust standard errors clustered by sector in parentheses; All estimates include Country and Sector dummies; *Omitted categories are firms that do not exhibit the respective internet attributes, large firms, firms that have not introduced a new process, firms which do not have at least 10% of foreign ownership, firms that do not export at least 10% of its sales, and firms located in smallest locations; * Significant at 10%. ** Significant at 5%. *** Significant at 1%*

Figure 1: log(TFP) kernel density (2010) by internet adoption and use



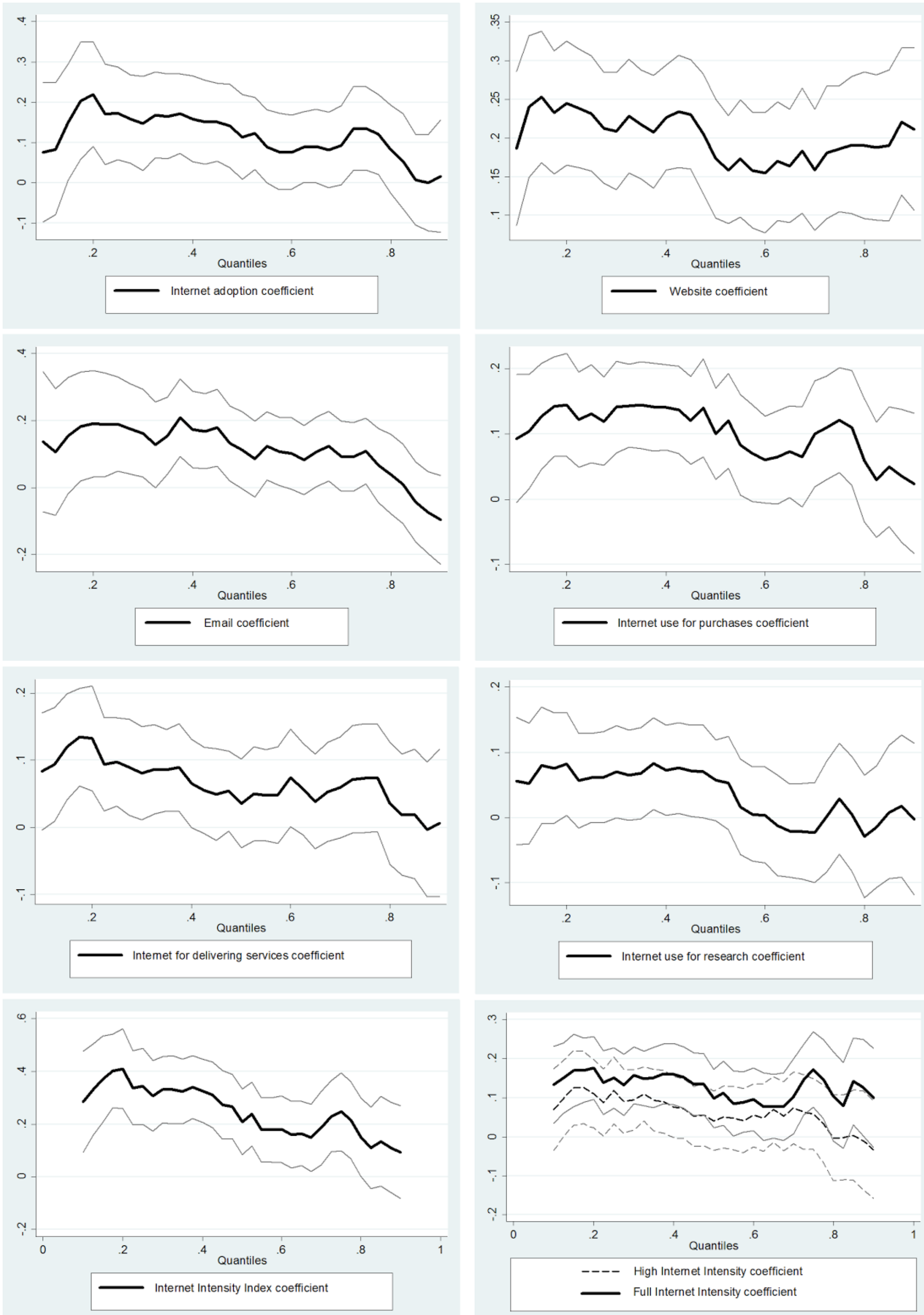
Source: authors own elaboration

Figure 2: log(TFP) kernel density (2010) by Internet Intensity



Source: authors own elaboration

Figure 3: UQR estimated coefficients of internet variables



Source: authors own elaboration

Appendix

Construction of the firm TFP measure

Different approaches were considered for building the TFP series: Ordinary Least Squares (OLS), Fixed Effects (FE), Olley-Pakes (OP), and Levinsohn-Petrin (LP). In the case of OP, we used investment (in logs) as proxy for unobservable productivity shocks. In the estimation under LP, the log of materials was used for that purpose. These estimations were conducted only for comparison purposes, considering the complete sample (no sector-level estimation), because of missing observations for the OP estimator, which resulted in the impossibility to estimate considerable sectors. Table A.1 summarizes the results for the Cobb-Douglas production function estimates.

Before analyzing the results, an important issue arising here is that OP estimation was based on much fewer observations that the rest of the cases, because the investment proxy was missing or zero in much cases. OP and LP report similar results for the physical capital coefficient (although there are differences in the level of significance), but OP coefficient on labour seems to be larger. As in Van Beveren (2012), Fixed Effects estimation reports much lower coefficients. In this case, OLS reports the highest coefficients. After estimation, TFP series were constructed. Correlations of the different series of log(TFP) are exposed on Table A.2.

As seen in Table A.2, the LP TFP estimation is very highly correlated to those estimated through OP and FE. LP was chosen as the preferred approach as it controls for simultaneity while using as proxy intermediate inputs that adjust more smoothly to shocks tan investment.

Table A.3 summarizes the sectoral classification, which exhibit important differences in *K/L* and *Y/K* ratios among different sectors. Therefore, in order to reduce any potential bias, we computed the TFP series by running sector-specific regressions, as explained in the main text.

Robustness analysis

As done by other researchers, a possible measure to control endogeneity is to lag those regressors which can be the cause of those concerns. For instance, Seker (2012) tried to find out the impact of external commerce in innovation and in labour growth for a firm-level sample of emerging regions, using a 3-period lag of its export and import variables as a robustness check.

In our case, we have lagged email and website use variables for a subsample of 606 enterprises. Results are exposed in Table A.4, in comparison with those results using 2010 internet variables for the same subsample.

Parameters estimated for 2006 and 2010 seem to be close in comparison, which suggests that any estimation bias using internet contemporary data seem to be limited, assuming that the coefficient of the lagged variable allows to isolate the effect on TFP. This supposition seems to be verified when analyzing the partial correlation for website and email between its 2010 and 2006 levels (0.394 for website and 0.310 for email), computed after regressing the 2010 internet variables to the correspondent 2006 measure plus all other control variables. All this seems to validate main OLS results using 2010 internet variables as regressors.

For the IV estimations, we will consider different sets of instruments which, given data availability, seem to be appropriate for this case (details in Table A.5). In first place, we will build on the idea that broadband roll-outs (i.e.: ADSL or Cable Modem) rely on the copper wire of pre-existing voice-telephony networks. As stated by Czernich et al (2011), the required access to an existing infrastructure built for other purposes, such as that of fixed telephony, make this a suitable instrument for this estimation strategy. This strategy is similar to that followed by Bertschek et al (2013), which for a firm-level analysis uses ADSL availability as an instrument for broadband, and Czernich et al (2011), who uses fixed-line voice telephony and Cable TV pre-existing networks as instruments for broadband in a national-level analysis. In our case, the instrument to be used is the number of voice-telecommunication fixed access lines per 100 inhabitants ten years before, in interaction with firm characteristics such as age and size. In addition, to take into account differences in internet uses, country-level internet users per 100 inhabitants 10 years before will be added as instrument, in interaction with the same firm characteristics. The introduced instruments are heavily expected to be exogenous, as are national-level indicators, which avoids any influence which an individual firm may have, and were lagged considerably (10 years) to break any possibility of being affected by contemporary shocks.

The second group of instruments will be the lagged internet variables available. This approach has already been followed in the literature, for instance, Bresnahan et al (2002), while intending to find out the effect of Computerization on Human Capital investments for a firm-level analysis in the US, instrumented theirs IT variable with its 4-year lag. In our case, the only internet variables for which we have lags are website and email, from the 2006 wave of the survey. Sanchez et al (2006) for a firm level analysis in Spain which intended to find out the effect of internet on productivity, also used an own website indicator as an instrument for internet usage at work. This second group of instruments are supposed to be considerably correlated to the 2010 internet variables, and the only incidence in TFP is expected to take part through the instrumented variable, while the 4 year lag should mitigate any concern of reverse causality. Therefore, this set of instruments are widely expected to be strong, although it still remains to be verified if they fulfill with the exclusion restrictions, as may be affected by some unobservables which may also have an incidence on TFP.

Finally, the third group of instruments will be a mix of the previous two: on the one hand the number of voice-telecommunication fixed access lines per 100 inhabitants ten years before, in interaction with firm characteristics such as age and size; plus the lagged website and email values from 2006. For the reasons described above, this set of instruments should be strong, while overall exogeneity should be verified.

Results are shown at Tables A.6 to A.8. All estimations were performed following the IV-LIML approach, which has proven to be more suitable in the presence of weak instruments. In any case, it has to be said that is complicated to interpret the results as in considerable cases the instruments do not seem to be valid. As seen in Tables A.6 to A.8, in all estimations the results suggest that instrumental variables approach resulted in higher coefficients, although less precise than OLS as the standard errors increase considerably. This is similar to the findings of Czernich et al (2011) for a national-level analysis, and Bertschek et al (2013) for a firm-level approach.

The estimations performed with the first group of instruments (Table A.6) clearly verify the exogeneity conditions, as suggested by the Overidentification contrasts, but on the other hand, fears seem to be confirmed with respect to its weaknesses, as suggested by the weak instrument contrast. As a result, while the exclusion restrictions are clearly fulfilled, the instruments do not seem to be closely enough related to the internet variables, then casting doubts over the results. Despite that, coefficients associated to internet adoption, email, and website appear to be positive and statistically significant. The only estimations of this group that seem to slightly overcome the weak identification test are those shown in columns (iv) (internet for purchases), (v) (internet for delivering services) and (vii) (intensity indicator), although standard deviation is so large that the coefficients remain insignificant. The estimations performed with the second group of instruments (Table A.7) seem to provide strong results, as instruments seem to be strongly correlated with the internet variables, and higher significance levels are achieved in the respective coefficients, but on the other hand, concerns arise regarding the exogeneity of the instruments, as seen in the Overidentification contrast. In this case, only the estimations represented in columns (ii) (website use), (iv) (internet use for purchases) and (vii) (intensity index) seem to verify the double condition of strong instruments and exclusion restrictions. Finally, the third group of instruments (Table A.8) seem to verify the double condition for columns (ii) (website), (v) (internet for delivering services), (vi) (internet use for research), and (vii) (intensity index) which suggest a positive and significant effect on TFP in most cases, with the exception of internet use for research, something which is aligned with the OLS results described at the main text.

To sum up, while difficult to reach a definitive conclusion, the results described above seem to suggest that the OLS estimations may be underestimating the true effect of ICT on TFP. This has already been verified in similar situations exposed in other articles, such as Czernich et al (2011) and Bertschek et al (2013).

Unconditional Quantile Regressions

Table A.9 summarizes the results for the UQR estimates. Only coefficients associated to internet variables are exposed, for the sake of simplicity[15].

[15] Complete results available upon request.

Table A.1 - Production function estimates

	OLS	Fixed Effects	Olley-Pakes	Levinsohn-Petrin
log(K)	0.082***	0.046**	0.056*	0.053***
	[0.005]	[0.019]	[0.029]	[0.020]
log(L)	0.926***	0.636***	0.893***	0.773***
	[0.006]	[0.036]	[0.009]	[0.011]
Observations	7799	7799	4461	7776

Source: authors own elaboration

Table A.2 - Correlation of TFP estimators

	log TFP (OP)	log TFP (LP)	log TFP (FE)	log TFP (OLS)
log TFP (OP)	1.00			
log TFP (LP)	0.95	1.00		
log TFP (FE)	0.84	0.96	1.00	
log TFP (OLS)	0.99	0.89	0.74	1.00

Source: authors own elaboration

Table A.3 - Sectoral classification - "Intermediate-level SNA/ISIC aggregation"

Aggregation code	Sector	Obs.	*K/L*	*Y/K*
4	Manufacture of textiles, wearing apparel, leather and related products	1860	4.10	15.47
5	Manufacture of wood and paper products; printing and reproduction of recorded media	1774	3.46	77.65
6	Manufacture of coke and refined petroleum products	120	1.45	13.61
7	Manufacture of chemicals and chemical products	155	3.25	21.10
8	Manufacture of basic pharmaceutical products and pharmaceutical preparations	62	8.91	7.63
9	Manufacture of rubber and plastics products, and other non-metallic mineral products	210	3.06	7.99
10	Manufacture of basic metals and fabricated metal products, except machinery and equipment	1412	3.44	25.45
11	Manufacture of computer, electronic and optical products	391	3.58	14.59
12	Manufacture of electrical equipment	96	5.01	9.100
13	Manufacture of machinery and equipment n.e.c.	747	2.95	17.82
14	Manufacture of transport equipment	423	9.24	55.13
15	Other manufacturing; repair and installation of machinery and equipment	161	2.80	13.87
16	Electricity, gas, steam and air conditioning supply	14	1.51	11.89
17	Water supply; sewerage, waste management and remediation	303	1.52	16.91
19	Wholesale and retail trade; repair of motor vehicles and motorcycles	6	1.39	6.75
20	Transportation and storage	18	4.44	18.60
22	Publishing, audiovisual and broadcasting activities	1	7.29	1.00
24	IT and other information services	2	2.00	2.39
28	Scientific research and development	2	1.66	1.17

Source: authors own elaboration

Table A.4 - OLS estimations with lagged internet variables

Website 2006	0.218***		0.203***			
	[0.053]		[0.056]			
Email 2006		0.164***	0.089			
		[0.055]	[0.056]			
Website 2010				0.296***		0.287***
				[0.061]		[0.061]
Email 2010					0.200***	0.121
					[0.073]	[0.079]
Micro size	-0.954***	-1.021***	-0.934***	-0.919***	-1.052***	-0.911***
	[0.151]	[0.145]	[0.147]	[0.142]	[0.155]	[0.144]
Small size	-0.572***	-0.623***	-0.565***	-0.566***	-0.642***	-0.567***
	[0.115]	[0.115]	[0.112]	[0.106]	[0.121]	[0.107]
Medium size	-0.338***	-0.370***	-0.336***	-0.351***	-0.385***	-0.356***
	[0.095]	[0.096]	[0.094]	[0.091]	[0.100]	[0.092]
Human Capital	0.004**	0.005**	0.004**	0.004**	0.005**	0.004**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Manager Experience	-0.001	-0.001	-0.001	-0.001	0.000	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Innovation	0.010	0.009	-0.009	-0.004	0.008	-0.006
	[0.047]	[0.050]	[0.047]	[0.045]	[0.050]	[0.045]
Age	0.002	0.002	0.002	0.002	0.002	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
FDI	0.336***	0.324***	0.339***	0.346***	0.317***	0.346***
	[0.116]	[0.117]	[0.116]	[0.121]	[0.116]	[0.120]
Export	0.013	0.052	0.014	0.009	0.052	0.008
	[0.070]	[0.072]	[0.071]	[0.078]	[0.072]	[0.078]
Capital City	0.162	0.125	0.151	0.118	0.130	0.111
	[0.127]	[0.124]	[0.127]	[0.129]	[0.124]	[0.129]
Big City	0.117	0.075	0.105	0.106	0.086	0.101
	[0.123]	[0.126]	[0.123]	[0.127]	[0.125]	[0.128]
Medium City	0.105	0.046	0.098	0.067	0.059	0.070
	[0.170]	[0.168]	[0.167]	[0.169]	[0.168]	[0.167]
Small City	0.347*	0.315*	0.339*	0.309*	0.324*	0.307
	[0.184]	[0.186]	[0.186]	[0.184]	[0.184]	[0.184]
R-squared	0.586	0.577	0.587	0.592	0.577	0.593
Observations	606	606	606	606	606	606

*Notes: Estimated coefficients from the regressions; Robust standard errors (clustered by sector) in parentheses; All estimates include Country and Sector dummies; Omitted categories are firms that do not exhibit the respective internet attributes, large firms, firms that have not introduced a new process, firms which do not have at least 10% of foreign ownership, firms that do not export at least 10% of its sales, and firms located in smallest locations; * Significant at 10% . ** Significant at 5% . *** Significant at 1%*

Table A.5 - Instruments used

Instrument Group	Detail
Group 1	*TEF2000*micro*age1, TEF2000*small*age1, TEF2000*medium*age1, TEF2000*big*age1, TEF2000*micro*age2, TEF2000*small*age2, TEF2000*medium*age2, TEF2000*big*age2, TEF2000*micro*age3, TEF2000*small*age3, TEF2000*medium*age3, TEF2000*big*age3, TEF2000*micro*age4, TEF2000*small*age4, TEF2000*medium*age4, INT2000*micro*age1, INT2000*small*age1, INT2000*medium*age1, INT2000*big*age1, INT2000*micro*age2, INT2000*small*age2, INT2000*medium*age2, INT2000*big*age2, INT2000*micro*age3, INT2000*small*age3, INT2000*medium*age3, INT2000*big*age3, INT2000*micro*age4, INT2000*small*age4, INT2000*medium*age4*
Group 2	*Website (2006), Email (2006)*
Group 3	*TEF2000*micro*age1, TEF2000*small*age1, TEF2000*medium*age1, TEF2000*big*age1, TEF2000*micro*age2, TEF2000*small*age2, TEF2000*medium*age2, TEF2000*big*age2, TEF2000*micro*age3, TEF2000*small*age3, TEF2000*medium*age3, TEF2000*big*age3, TEF2000*micro*age4, TEF2000*small*age4, TEF2000*medium*age4, Website (2006), Email (2006)*

Source: authors own elaboration

Note: TEF2000: National level voice-telecommunication fixed access lines per 100 inhabitants in year 2000, INT2000: National level internet users per 100 inhabitants in year 2000, age1: dummy that takes the value of 1 if age<5, age2: dummy that takes the value of 1 if age>=5 & age<10, age3: dummy that takes the value of 1 if age>=10 & age<20, age4: dummy that takes the value of 1 if age>=20.

Table A.6 - Instrumental Variables estimates (Group 1 of instruments)

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Internet adoption	0.613**						
	[0.309]						
Website		1.190**					
		[0.567]					
E-mail			0.686*				
			[0.408]				
Internet used for purchases				0.182			
				[0.445]			
Internet used for delivering services					0.491		
					[0.436]		
Internet used for research						0.681	
						[0.446]	
Internet intensity index							0.631
							[0.412]
Micro size	-0.799***	-0.318	-0.842***	-0.891***	-0.869***	-0.786***	-0.773***
	[0.086]	[0.316]	[0.083]	[0.154]	[0.095]	[0.119]	[0.133]
Small size	-0.571***	-0.257	-0.598***	-0.597***	-0.597***	-0.550***	-0.545***
	[0.056]	[0.178]	[0.049]	[0.061]	[0.050]	[0.064]	[0.067]
Medium size	-0.293***	-0.174**	-0.304***	-0.301***	-0.304***	-0.283***	-0.287***
	[0.044]	[0.076]	[0.042]	[0.043]	[0.043]	[0.051]	[0.045]
Human Capital	0.004***	0.002	0.004***	0.004***	0.004***	0.004***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Manager Experience	-0.001	-0.001	-0.001*	-0.001*	-0.002*	-0.001	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Process innovation	0.019	-0.051	0.014	0.027	0.001	-0.035	-0.009
	[0.022]	[0.058]	[0.030]	[0.046]	[0.044]	[0.058]	[0.044]
Age	0.002***	0.000	0.002***	0.002***	0.002***	0.002***	0.002**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
FDI	0.154***	0.181***	0.141***	0.148***	0.154***	0.199***	0.164***
	[0.033]	[0.038]	[0.032]	[0.038]	[0.035]	[0.054]	[0.034]
Export	0.083**	0.038	0.097**	0.100**	0.089*	0.077*	0.082*
	[0.039]	[0.061]	[0.040]	[0.043]	[0.046]	[0.042]	[0.044]
Capital City	0.116**	0.086	0.100*	0.124**	0.097*	0.128*	0.112**
	[0.058]	[0.056]	[0.053]	[0.052]	[0.058]	[0.066]	[0.054]
Big City	0.130*	0.131*	0.118*	0.122*	0.122*	0.105	0.121*
	[0.071]	[0.069]	[0.068]	[0.065]	[0.068]	[0.080]	[0.067]
Medium City	0.123*	0.156**	0.097	0.088	0.106	0.121	0.109*
	[0.073]	[0.077]	[0.067]	[0.061]	[0.065]	[0.079]	[0.065]
Small City	0.128*	0.146**	0.144**	0.128*	0.098	0.140**	0.134**
	[0.065]	[0.070]	[0.065]	[0.066]	[0.063]	[0.064]	[0.061]
Observations	3587	3595	3594	3587	3587	3587	3585
Over-id statistic	36.232	23.219	33.229	34.917	28.977	32.786	33.375
Weak Identification test	3.681	2.303	2.589	7.926	5.092	2.134	5.123

*Source: authors own elaboration. Notes: Estimated coefficients from the regressions; Robust standard errors (clustered by sector) in parentheses; All estimates include Country and Sector dummies; Omitted categories are firms that do not exhibit the respective internet attributes, large firms, firms that have not introduced a new process, firms which do not have at least 10% of foreign ownership, firms that do not export at least 10% of its sales, and firms located in smallest locations; Stock-Yogo weak ID test critical values: 10% maximal LIML size: 3.870, * Significant at 10%. ** Significant at 5%. *** Significant at 1%*

Table A.7 - Instrumental Variables estimates (Group 2 of instruments)

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Internet adoption	0.951*						
	[0.523]						
Website		0.549***					
		[0.137]					
E-mail			0.571**				
			[0.230]				
Internet used for purchases				1.117***			
				[0.375]			
Internet used for delivering services					0.980***		
					[0.367]		
Internet used for research						0.992**	
						[0.468]	
Internet intensity index							0.874***
							[0.234]
Micro size	-0.874***	-0.787***	-1.015***	-0.764***	-0.848***	-0.821***	-0.832***
	[0.130]	[0.111]	[0.139]	[0.149]	[0.177]	[0.156]	[0.121]
Small size	-0.559***	-0.499***	-0.635***	-0.600***	-0.5212***	-0.510***	-0.545***
	[0.097]	[0.082]	[0.110]	[0.122]	[0.117]	[0.112]	[0.091]
Medium size	-0.357***	-0.328***	-0.396***	-0.535***	-0.428***	-0.333***	-0.391***
	[0.092]	[0.075]	[0.094]	[0.140]	[0.126]	[0.103]	[0.091]
Human Capital	0.003**	0.004**	0.005***	0.002	0.005***	0.004**	0.004**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Manager Experience	-0.001	-0.001	0.000	-0.001	0.001	0.002	0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]
Process innovation	-0.018	-0.018	-0.002	-0.093	-0.041	-0.091	-0.047
	[0.050]	[0.043]	[0.048]	[0.082]	[0.069]	[0.078]	[0.052]
Age	0.002	0.001	0.002	0.002	0.002	0.002*	0.002
	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]
FDI	0.355***	0.372***	0.319***	0.315***	0.385***	0.441***	0.368***
	[0.106]	[0.111]	[0.104]	[0.113]	[0.114]	[0.137]	[0.103]
Export	-0.001	-0.031	0.044	-0.017	0.008	-0.033	-0.012
	[0.076]	[0.073]	[0.067]	[0.095]	[0.074]	[0.085]	[0.071]
Capital City	0.166	0.096	0.107	0.332*	0.352**	0.239	0.120
	[0.150]	[0.129]	[0.116]	[0.193]	[0.177]	[0.207]	[0.137]
Big City	0.103	0.117	0.072	0.112	0.216	0.155	0.128
	[0.138]	[0.121]	[0.117]	[0.192]	[0.180]	[0.213]	[0.140]
Medium City	0.200	0.080	0.070	0.245	0.373	0.185	0.179
	[0.203]	[0.154]	[0.148]	[0.211]	[0.228]	[0.205]	[0.155]
Small City	0.317	0.293*	0.316*	0.413*	0.498**	0.519**	0.389**
	[0.204]	[0.175]	[0.171]	[0.264]	[0.216]	[0.251]	[0.188]
Observations	605	606	606	605	605	605	605
Over-id statistic	5.652**	0.040	6.632**	3.480*	4.651**	3.983**	3.072*
Weak Identification test	7.176	48.999	13.103	8.373	8.211	8.140	28.144

*Source: authors own elaboration. Notes: Estimated coefficients from the regressions; Robust standard errors (clustered by sector) in parentheses; All estimates include Country and Sector dummies; Omitted categories are firms that do not exhibit the respective internet attributes, large firms, firms that have not introduced a new process, firms which do not have at least 10% of foreign ownership, firms that do not export at least 10% of its sales, and firms located in smallest locations; Stock-Yogo weak ID test critical values: 10% maximal LIML size: 8.680; * Significant at 10%. ** Significant at 5%. *** Significant at 1%*

Table A.8 - Instrumental Variables estimates (Group 3 of instruments)

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Internet adoption	1.033*						
	[0.598]						
Website		0.552***					
		[0.130]					
E-mail			0.528**				
			[0.245]				
Internet used for purchases				0.895**			
				[0.367]			
Internet used for delivering services					0.592**		
					[0.292]		
Internet used for research						0.542	
						[0.367]	
Internet intensity index							0.773***
							[0.230]
Micro size	-0.857***	-0.785***	-1.019***	-0.826***	-0.938***	-0.936***	-0.860***
	[0.128]	[0.111]	[0.137]	[0.163]	[0.160]	[0.125]	[0.127]
Small size	-0.552***	-0.498***	-0.636***	-0.609***	-0.572***	-0.572***	-0.556***
	[0.097]	[0.081]	[0.110]	[0.119]	[0.111]	[0.088]	[0.093]
Medium size	-0.356***	-0.328***	-0.394***	-0.503***	-0.406***	-0.351***	-0.389***
	[0.092]	[0.075]	[0.094]	[0.126]	[0.105]	[0.089]	[0.090]
Human Capital	0.003**	0.004**	0.005***	0.003	0.005***	0.004**	0.004**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Manager Experience	-0.001	-0.001	0.000	-0.001	0.000	0.001	0.000
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]
Process innovation	-0.020	-0.018	0.000	-0.072	-0.020	-0.045	-0.040
	[0.051]	[0.043]	[0.049]	[0.073]	[0.056]	[0.066]	[0.051]
Age	0.002	0.001	0.002	0.002	0.002	0.002*	0.002
	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]
FDI	0.359***	0.372***	0.319***	0.315***	0.357***	0.383***	0.362***
	[0.107]	[0.112]	[0.104]	[0.108]	[0.109]	[0.120]	[0.105]
Export	-0.006	-0.032	0.045	-0.003	0.026	0.006	-0.004
	[0.079]	[0.073]	[0.067]	[0.087]	[0.069]	[0.075]	[0.070]
Capital City	0.168	0.096	0.109	0.294*	0.268*	0.194	0.193
	[0.155]	[0.129]	[0.116]	[0.170]	[0.163]	[0.153]	[0.133]
Big City	0.105	0.117	0.073	0.107	0.165	0.124	0.123
	[0.143]	[0.121]	[0.117]	[0.169]	[0.157]	[0.155]	[0.136]
Medium City	0.212	0.080	0.069	0.208	0.248	0.128	0.165
	[0.210]	[0.154]	[0.148]	[0.182]	[0.206]	[0.174]	[0.154]
Small City	0.316	0.293*	0.317*	0.3952*	0.428**	0.430**	0.381**
	[0.209]	[0.175]	[0.171]	[0.237]	[0.192]	[0.206]	[0.184]
Observations	605	606	606	605	605	605	605
Over-id statistic	14.927	17.234	15.702	17.842	16.168	14.782	18.238
Weak Identification test	2.033	8.801	2.387	3.350	3.707	4.661	6.471

*Source: authors own elaboration. Notes: Estimated coefficients from the regressions; Robust standard errors (clustered by sector) in parentheses; All estimates include Country and Sector dummies; Omitted categories are firms that do not exhibit the respective internet attributes, large firms, firms that have not introduced a new process, firms which do not have at least 10% of foreign ownership, firms that do not export at least 10% of its sales, and firms located in smallest locations; Stock-Yogo weak ID test critical values: 10% maximal LIML size: 3.360; * Significant at 10%. ** Significant at 5%. *** Significant at 1%*

Table A.9 - UQR estimates

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Internet adoption	0.076	0.220***	0.148**	0.159***	0.114**	0.076	0.093*	0.083	0.016
	[0.089]	[0.066]	[0.060]	[0.054]	[0.054]	[0.047]	[0.050]	[0.056]	[0.071]
Website	0.187***	0.245***	0.209***	0.227***	0.173***	0.155***	0.159***	0.191***	0.211***
	[0.051]	[0.041]	[0.039]	[0.035]	[0.039]	[0.079]	[0.040]	[0.048]	[0.054]
Email	0.138	0.191**	0.162**	0.174***	0.112*	0.102*	0.094*	0.040	-0.096
	[0.107]	[0.081]	[0.067]	[0.058]	[0.058]	[0.055]	[0.053]	[0.060]	[0.068]
Internet used for purchases	0.093*	0.144***	0.141***	0.140***	0.100***	0.061*	0.100**	0.059	0.024
	[0.050]	[0.040]	[0.036]	[0.033]	[0.036]	[0.03]	[0.041]	[0.048]	[0.055]
Internet for deliver services	0.084*	0.133***	0.081**	0.066*	0.035	0.074**	0.059	0.036	0.007
	[0.045]	[0.040]	[0.035]	[0.034]	[0.034]	[0.037]	[0.038]	[0.046]	[0.056]
Internet used for research	0.056	0.082**	0.070**	0.072**	0.057*	0.004	-0.023	-0.029	-0.002
	[0.050]	[0.040]	[0.036]	[0.035]	[0.032]	[0.038]	[0.039]	[0.048]	[0.059]
Internet intensity index	0.285***	0.410***	0.330 ***	0.326***	0.209***	0.181***	0.185***	0.151**	0.093
	[0.098]	[0.077]	[0.064]	[0.061]	[0.064]	[0.064]	[0.071]	[0.076]	[0.090]
High Internet intensity	0.069	0.110**	0.094**	0.076*	0.041	0.055	0.074	-0.004	-0.033
	[0.053]	[0.045]	[0.039]	[0.040]	[0.039]	[0.041]	[0.047]	[0.057]	[0.064]
Full Internet intensity	0.133***	0.176***	0.157***	0.161***	0.098***	0.096**	0.104**	0.103*	0.097
	[0.051]	[0.041]	[0.037]	[0.040]	[0.038]	[0.041]	[0.049]	[0.058]	[0.065]

Source: authors own elaboration

*Notes: Estimated coefficients from the regressions; Bootstraped standard errors in parentheses (400 reps); * Significant at 10%. ** Significant at 5%. *** Significant at 1%. All estimations include controls described in equation [1].*